Ocean turbulent fluxes from space: Using multi-platform passive microwave observations to generate products spanning the past to present

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Outline

- Fluxes from Space
- Challenges
- Climate Products
- Real-Time Products
- Future Improvements

Fluxes from Space

Relevance

Fundamentals

Empirical Models

Improving ocean evaporation estimates: Relevance

- Ocean evaporation remains the most uncertain component of the global water cycle in terms of both amplitude and percent-difference of observational estimates with "balance-constrained" optimal estimate

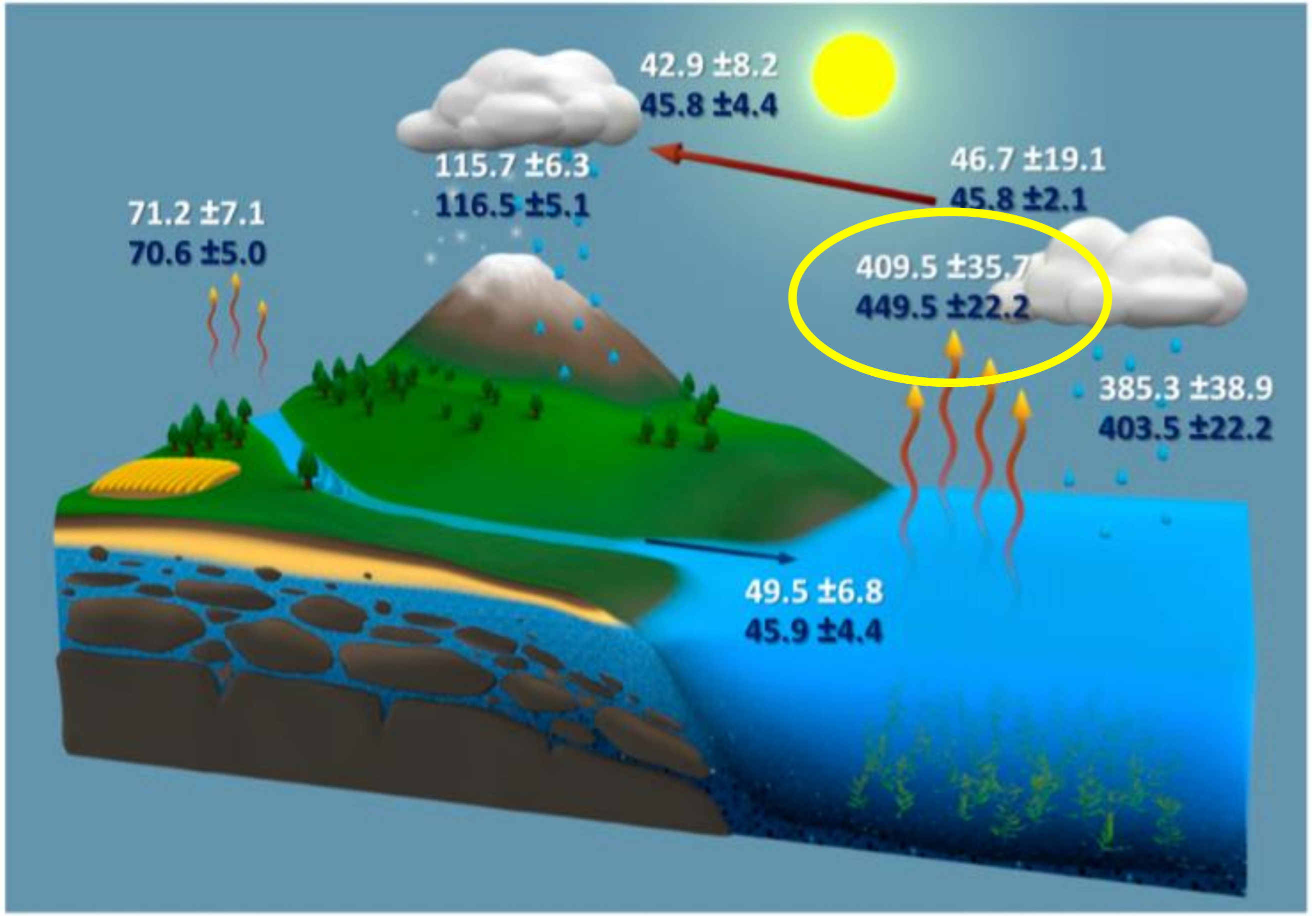
<u>NASA Water and Energy Cycle Focus Area</u>

- *How are global precipitation, evaporation, and the cycling of water changing?*

<u>GEWEX Data Assessment Panel (GDAP)</u>

- *How can we better measure and characterize the state and the variations of the climate using satellite observations?*
- *How do the internal water exchange and transport processes in the climate (a.k.a. water feedbacks) affect the climate's sensitivity?*

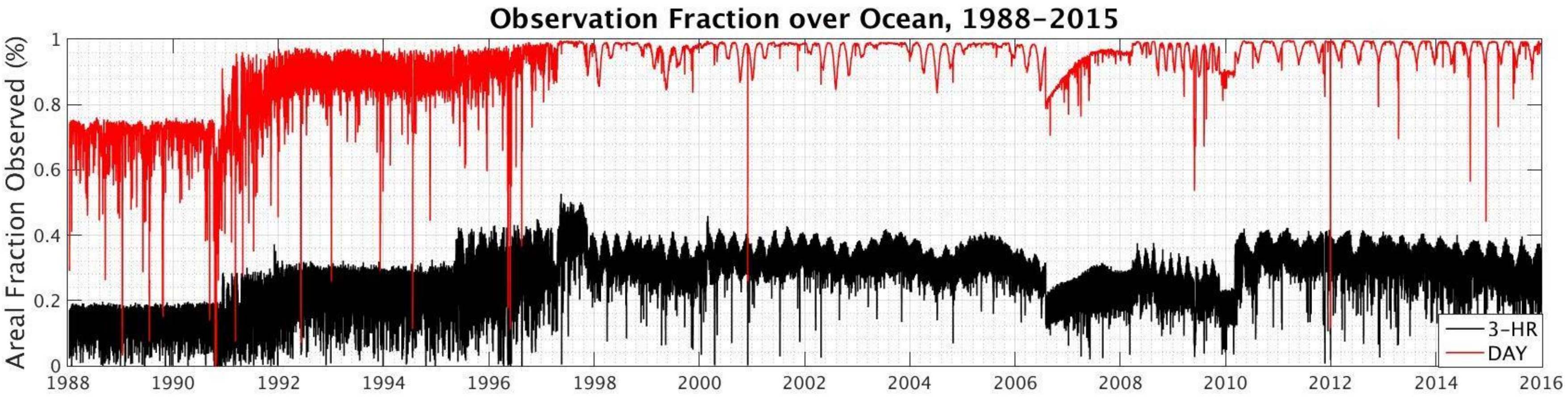
NEWS Climatology — Global Water Budget



From Rodell et al. (2015), The Observed State of the Water Cycle in the Early Twenty-First Century, J. Climate

Motivation

- In-situ surface observations from buoys and voluntary observing ships (VOS) constitute a valuable source of direct observations of surface meteorology required to estimate fluxes.
  - *However, they offer incomplete and highly variable coverage.*
  - *Coverage is further reduced when requiring all near-surface variables and measurement height metadata*
- Satellite based estimates provide an alternative approach with more complete global coverage every 1-2 days.
  - *The observational fraction of passive microwave sensors has changed over time as well, albeit with consistently more frequent and better global coverage.*



Observational fraction using only SSM/I and SSMIS, Global Ice-Free Ocean

Fluxes from Space: Basic Approach

$$LHF = \rho L_v C_e (Q_s(SST) - Q_{air})(Wspd)$$
$$SHF = \rho C_p C_h (SST - T_{air})(Wspd)$$

- Estimating the fluxes over the (ice-free) oceans reduces to i) retrieving each of the near-surface bulk variables and ii) application of a suitable bulk-flux algorithm (e.g. COARE 3.5).

Passive Microwave Sensors & Algorithms

- Each of the above parameters have been retrieved using passive microwave observations
- SST and surface winds directly impact the surface emission/pol properties
- 10-m Qair and Tair (i.e. at a specific level) show only moderate direct sensitivity and are more uncertain.

Sensor	Platform(s)	Period of Coverage	Intercalibration Effort	Algorithm Development
SSM/I	DMSP F08-F15	1987 – present	NOAA SSM/I FCDR	Liu (1986) Schulz (1993) Chou et al. (1995) Schluessel et al. (1995) Konda et al. (1996) Jones et al. (1999) Krasnopolsky et al. (2000). Bentamy et al. (2003) Jackson et al. (2006) Roberts et al. (2010)
SSMIS	DMSP F16-F18	2003 – present	NOAA SSMIS FCDR	
TMI	NASA TRMM	1998 – present	GPM Xcal	Kubota and Hihara (2008) Zong et al. (2007) Roberts et al. (2012)
AMSR-E	NASA AQUA	2002 – 2011	GPM Xcal	
WindSat	NRL Coriolis	2003 – present	GPM Xcal	
GMI	NASA GPM	2014 – present	GPM Xcal	
AMSU-A	N15 - N19; MetOp	1998 – present	NOAA AMSU FCDR	Shi (2001) Jackson et al. (2006) Jackson and Wick (2010)

Regression Approaches

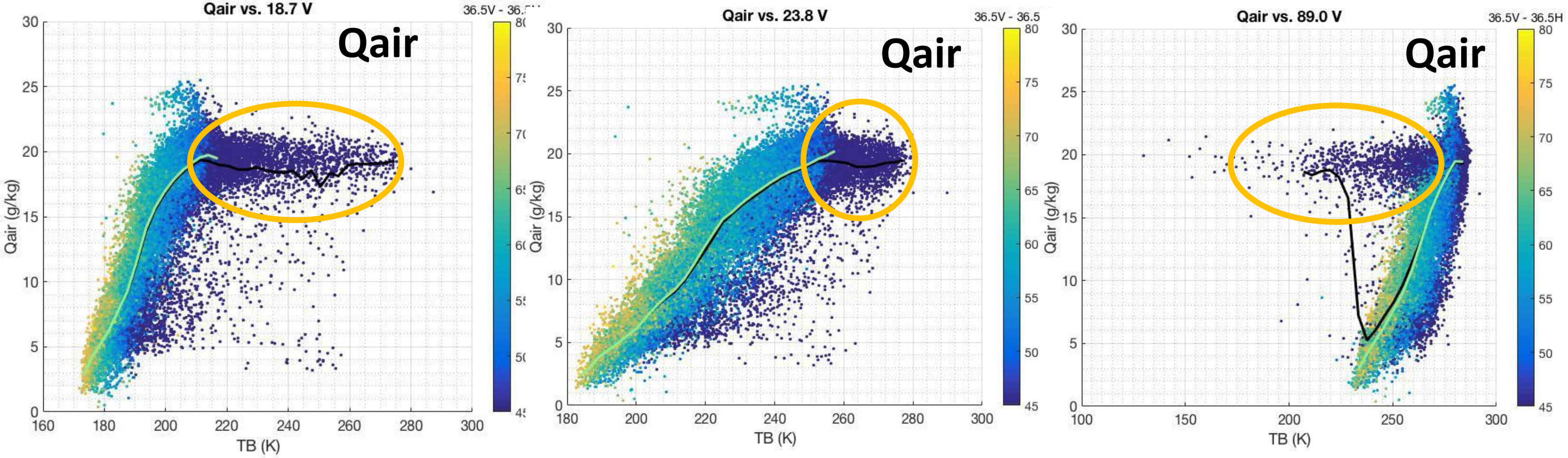
Empirical

- Obtain a paired training dataset of observed response variable and independent parameters (e.g. brightness temperatures) and attempt to model the relationship.

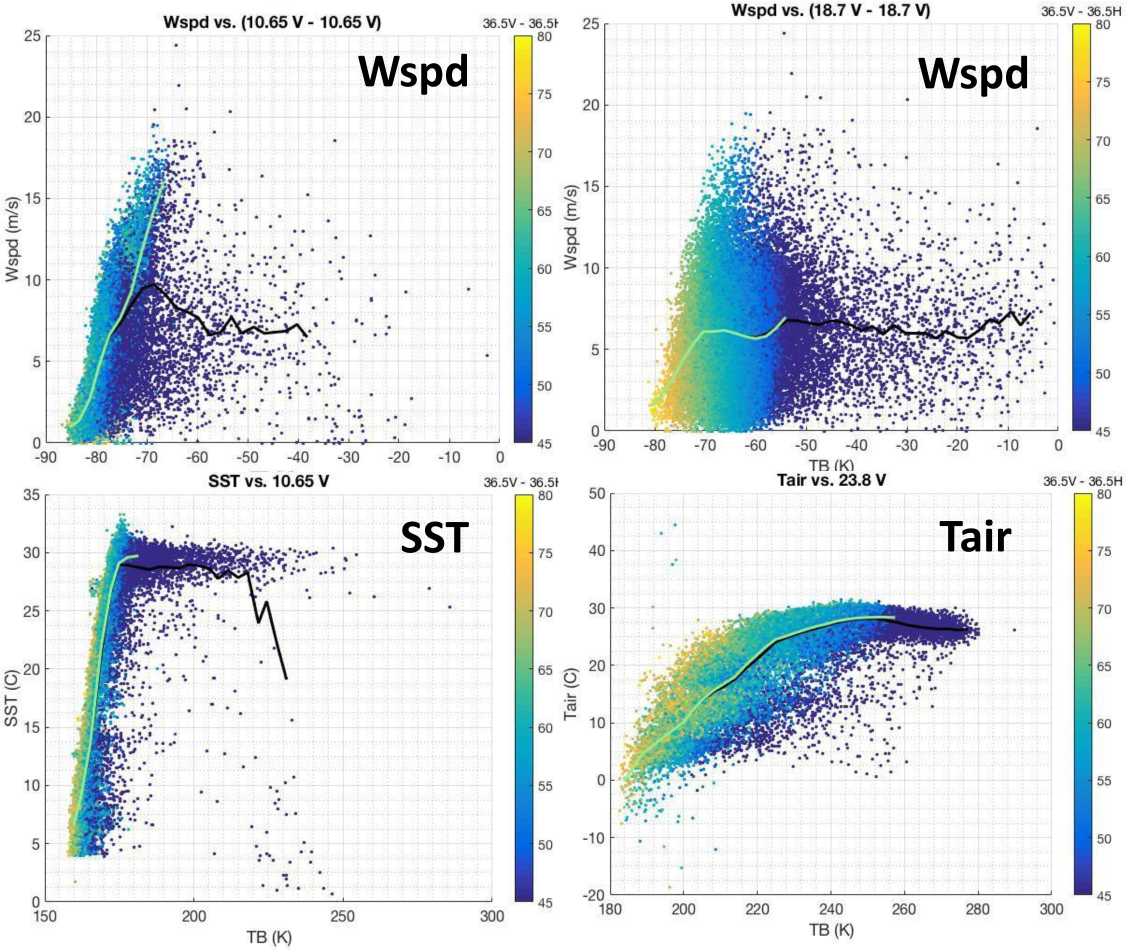
(SST, U10, PW, CLW, P, Qa , Ta,) = F(TB$_{10V}$, TB$_{10H}$,TB$_{19V}$, TB$_{19H}$, TB$_{22V}$, TB$_{37V}$, TB$_{37H}$, TB$_{85V}$, TB$_{85H}$)

From statistical decision theory, finding a "best" model for predicting a response variable—under squared error loss— results in the optimal solution (Hastie et al. 2009):
$\boldsymbol{f(x) = E(Y|X = x)}$***, i.e. the conditional expectation***

- Direct empirical methods make assumptions on the form of these conditional relationships and then estimate parameters of the model using a large paired dataset.
- All current satellite-based latent heat flux products use some form of empirical regression for specific humidity and/or wind speed, air temperature, sea surface temperature.
  - GSSTF 3.0, HOAPS 3.2, IFREMER 4.0, JOFURO 2.0, OAFlux 3.0, SEAFLUX-CDR 2.0



GMI Conditional Relationships: {Qair, Tair, Wspd, SST} vs. TB



- Must filter for thick clouds/rain impacts on satellite observations
  - (37V - 37H) < 45K ; Mask retrievals
- These show the *univariate* relationships between the near-surface values individual sensor channels. Regression retrievals will depend on the multivariate relationships.
- Information on surface air temperature is highly indirect, coming from it covariability with both sea surface temperature and humidity

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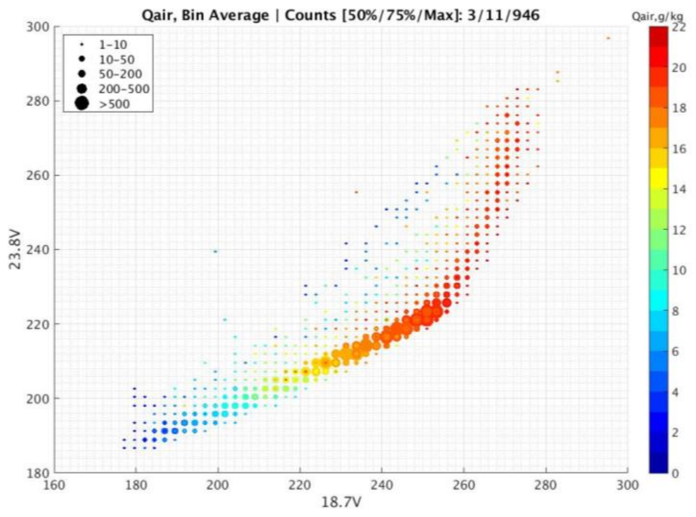
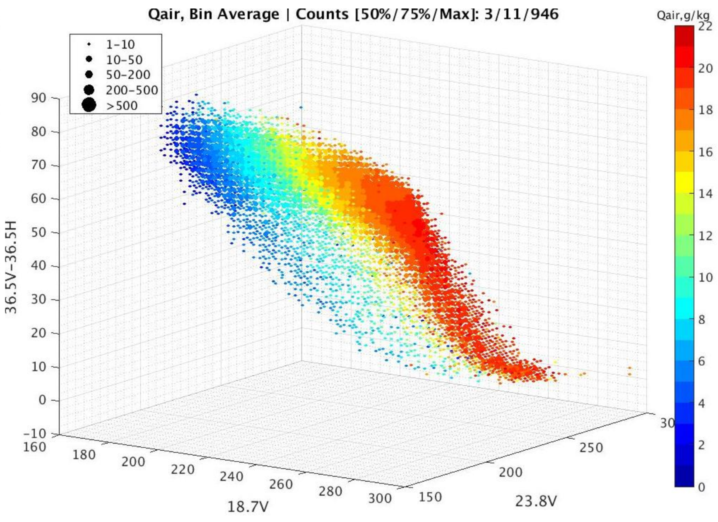
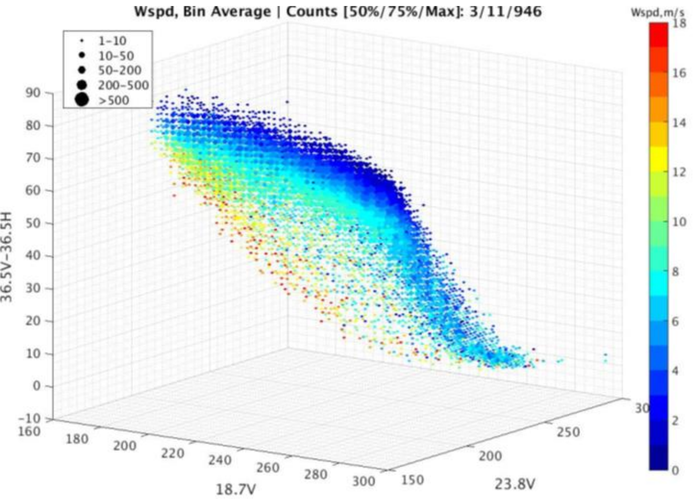






- Must filter for thick clouds/rain impacts on satellite observations
  - (37V - 37H) < 45K ; Mask retrievals
- These show the *multivariate* relationships between the near-surface values individual sensor channels. Regression retrievals will depend on the multivariate relationships.
- Information on surface air temperature is highly indirect, coming from it covariability with both sea surface temperature and humidity

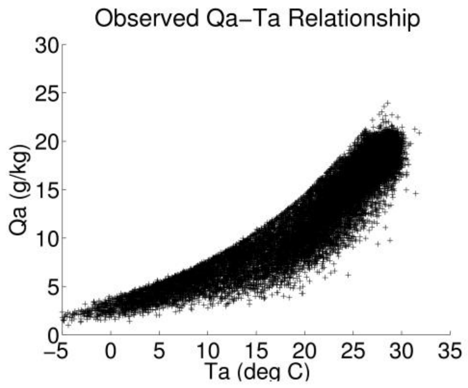
Regression - (Nonlinear) Neural Network

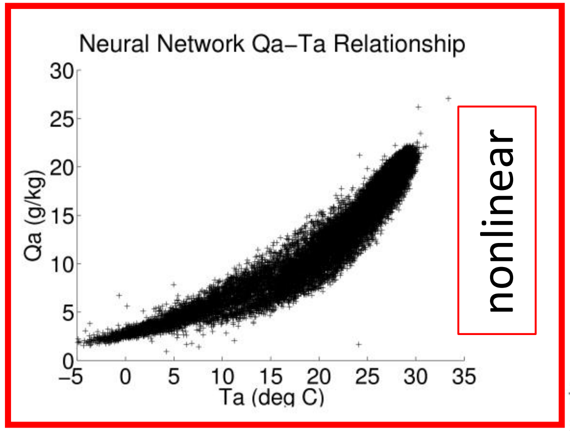
Multivariate Relationships

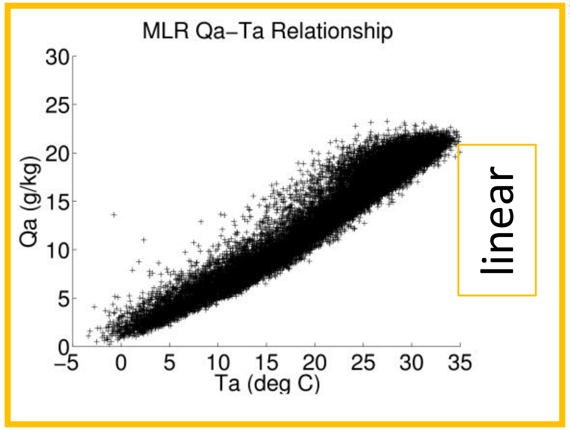
- Qair/Tair: Clausius-Clapeyron relationship imparts a strong connection
- SST/Tair: The sea surface temperature and air temperature are typically within ~1.5 K of one one another
- PW/Qair: Total columnar water vapor and surface air humidity are correlated.

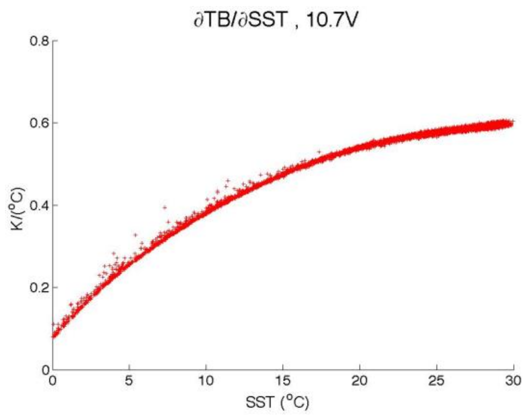
Nonlinearity

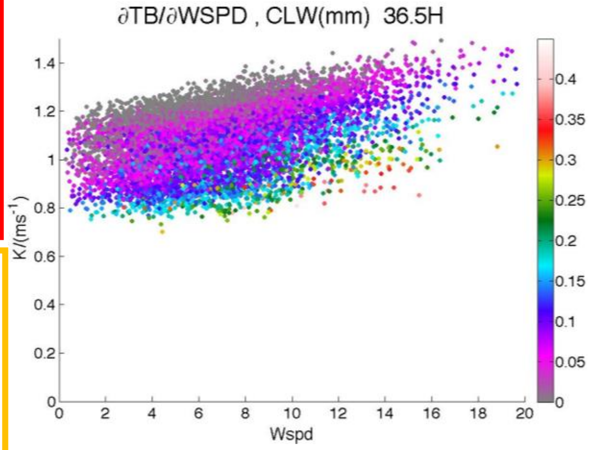
- Dependence on atmospheric state
- Dependence on surface conditions
- Inherent relationships between moisture and temperature.
- *Thus, we expect a nonlinear regression to be more appropriate for our regression model*



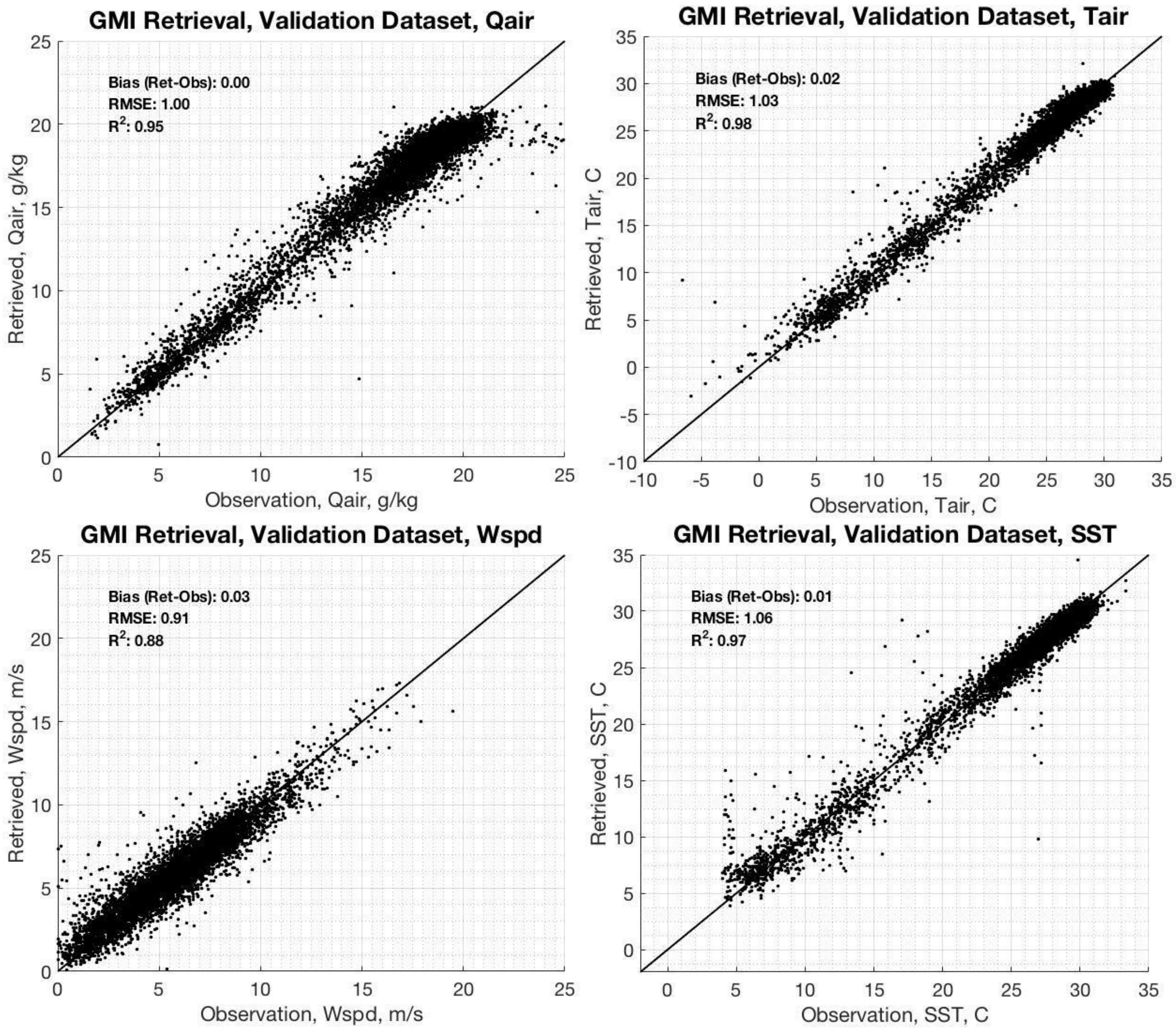








Results - Neural Network Retrieval



Model

[Qair, Tair, Wspd, SST] =
F_{NNET}(10V,10H,18V,18H,23V,36V-36H,89V-89H,RTG SST)
{37V-37H < 45K Masked}

Training

- Masking: Removes ~10% of values
- Results relatively insensitive to training algorithm structure and observational splitting into Training/Cross-Validation/Testing sets

Performance

- R^2 ~0.9 or better for all parameters
- Small bias and RMSE ~1.0 (g/kg, C, m/s) for all parameters
- Some outliers present; may require additional flagging

Challenges - Swath to Gridded Climate Data Records

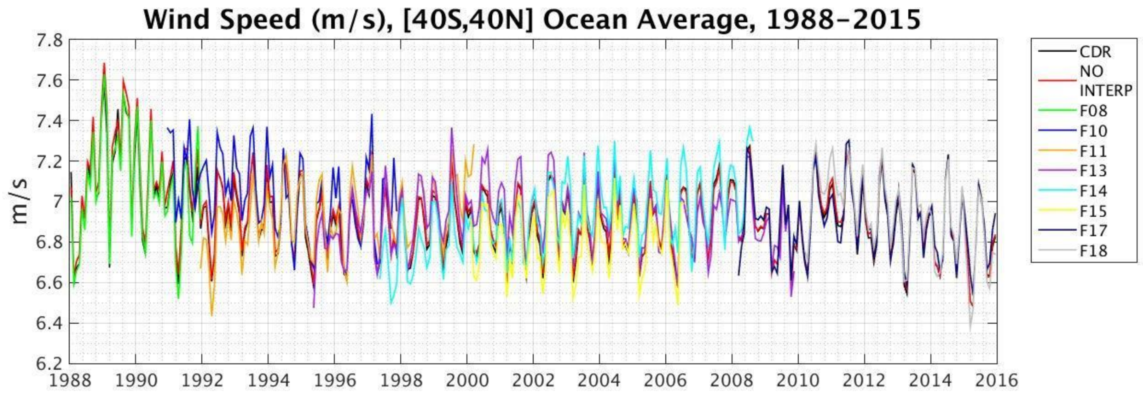
Intercalibration

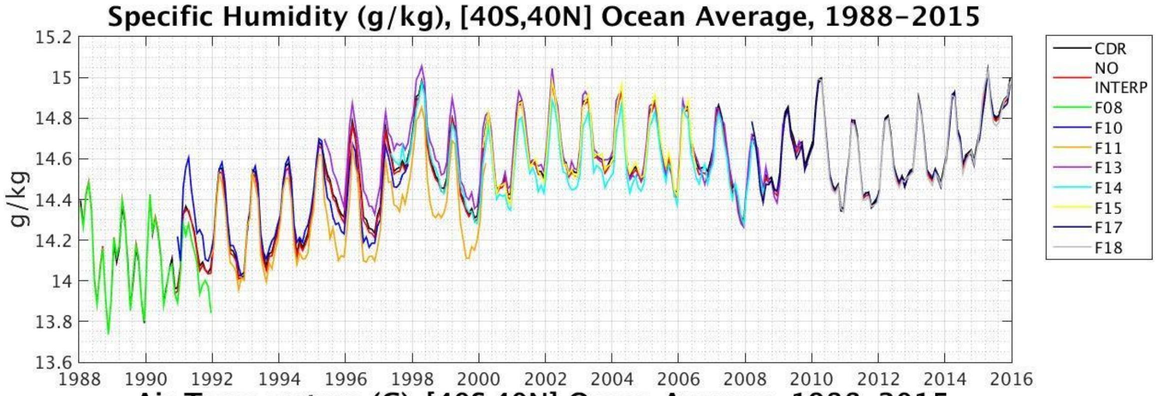
Earth View Angle Dependence

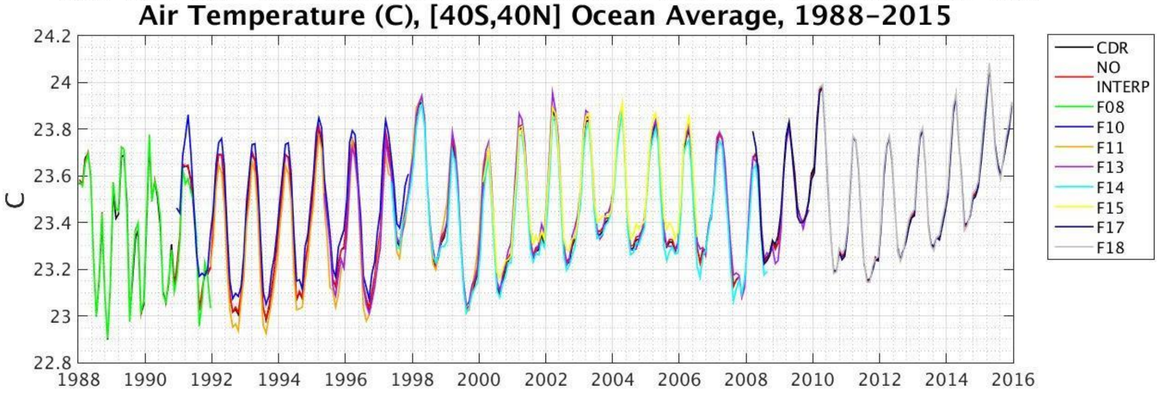
Gap-filling

Intercalibration

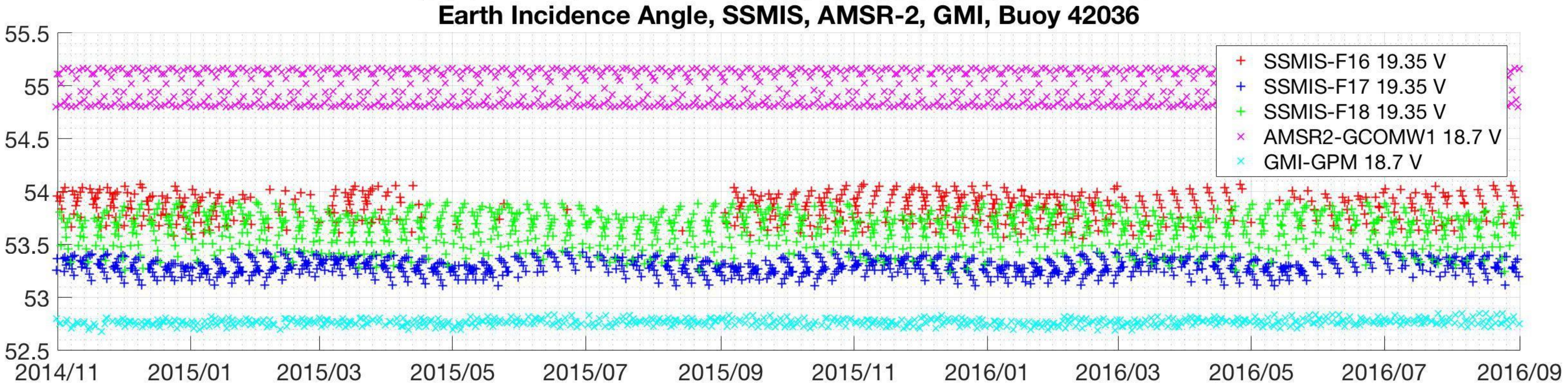
- Constructing a climate data record over a ~20-30 year period requires stitching together retrieved surface properties from multiple platforms and sensors
- For greatest consistency, it is best to use brightness temperatures that have been intercalibrated to a common reference standard
    - RSS v7 SSM/I and SSMIS CDR
    - *CSU FCDR (F13 as reference)*
    - GPM XCAL 1C (GMI as reference)
    - NOAA AMSU-A and Window FCDRs
- Intercalibration efforts result in TBs that are intercalibrated based on a common reference and forward model, but the data will still contain offsets due to physical differences (e.g. view-angle, central frequency)
- For empirical models, algorithms will still need to be tuned for a given sensor



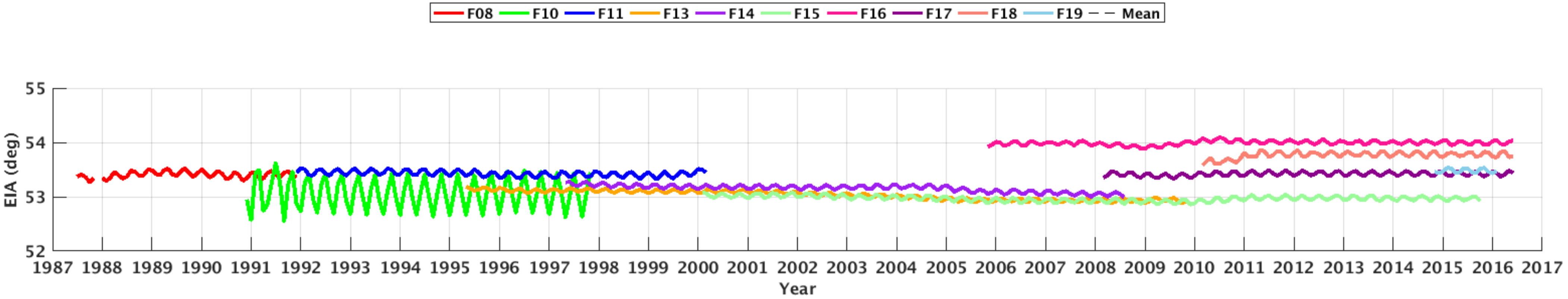




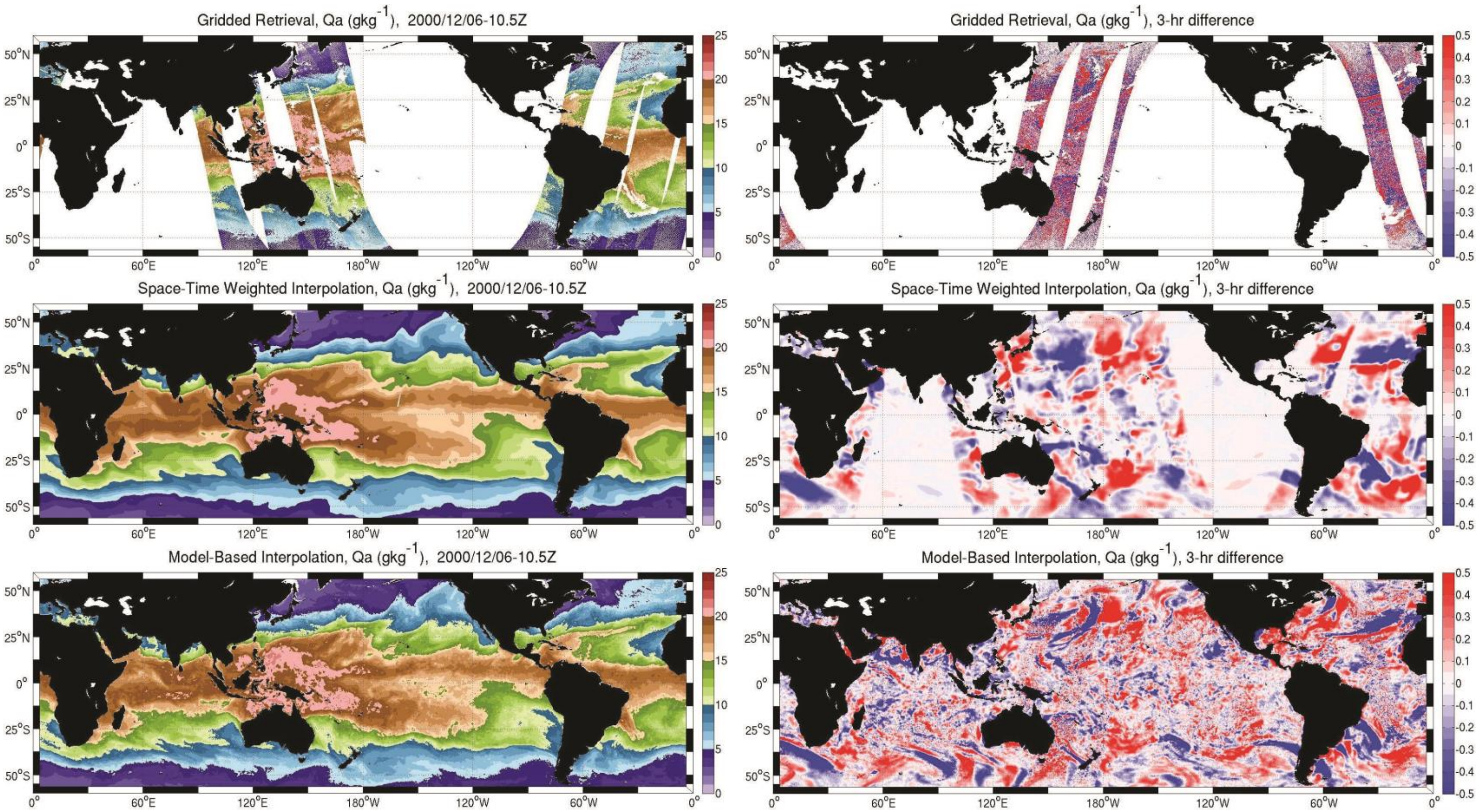
View Angle Dependence



- View-angles are often different between passive microwave imagers and they can change/drift during the lifetime of a single instrument



Gap-Filling



(left) Examples of the gridded, but non-interpolated surface humidity (Qa) retrieval, results using a simple space-time window weighted interpolation, and the results of MoBI.

(right) Examples of 3-hr differences of the same fields. Note how MoBI more smoothly captures the 3-hr evolution of high-latitude synoptic systems.

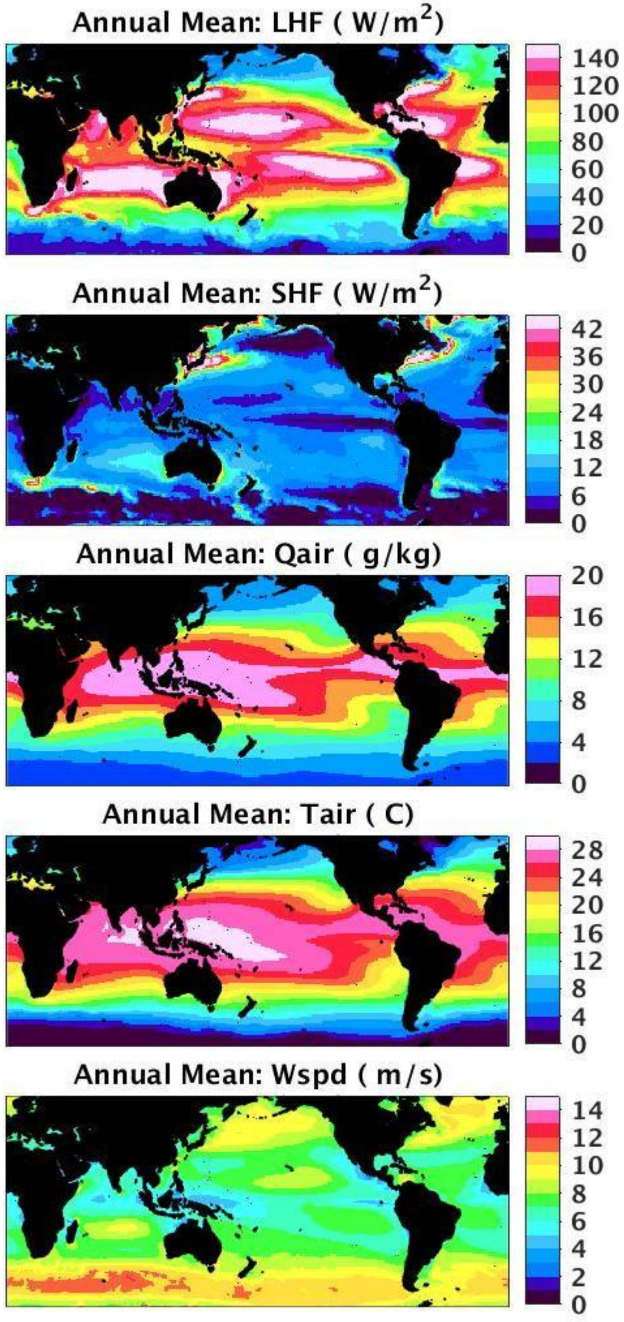
- Continued push to higher spatial and temporal resolution of derived products. End-users typically do not want to deal with "missing observations"; prefer the data provider to gap-fill missing data.

<u>Model-based Interpolation (MoBI) - Designed to capture the high-frequency evolution/advection-driven changes</u>

- Interpolates to unknown point (t) between observed satellite estimates at times A & B. Uses a weighted mean based on the difference between the satellite and model (MERRA-2) at observations and temporal distance between the observed points.
- Better maintains local spatial structure and temporal evolution than traditional space-time window based weighted interpolation.

Turbulent Fluxes - Climate Data Products

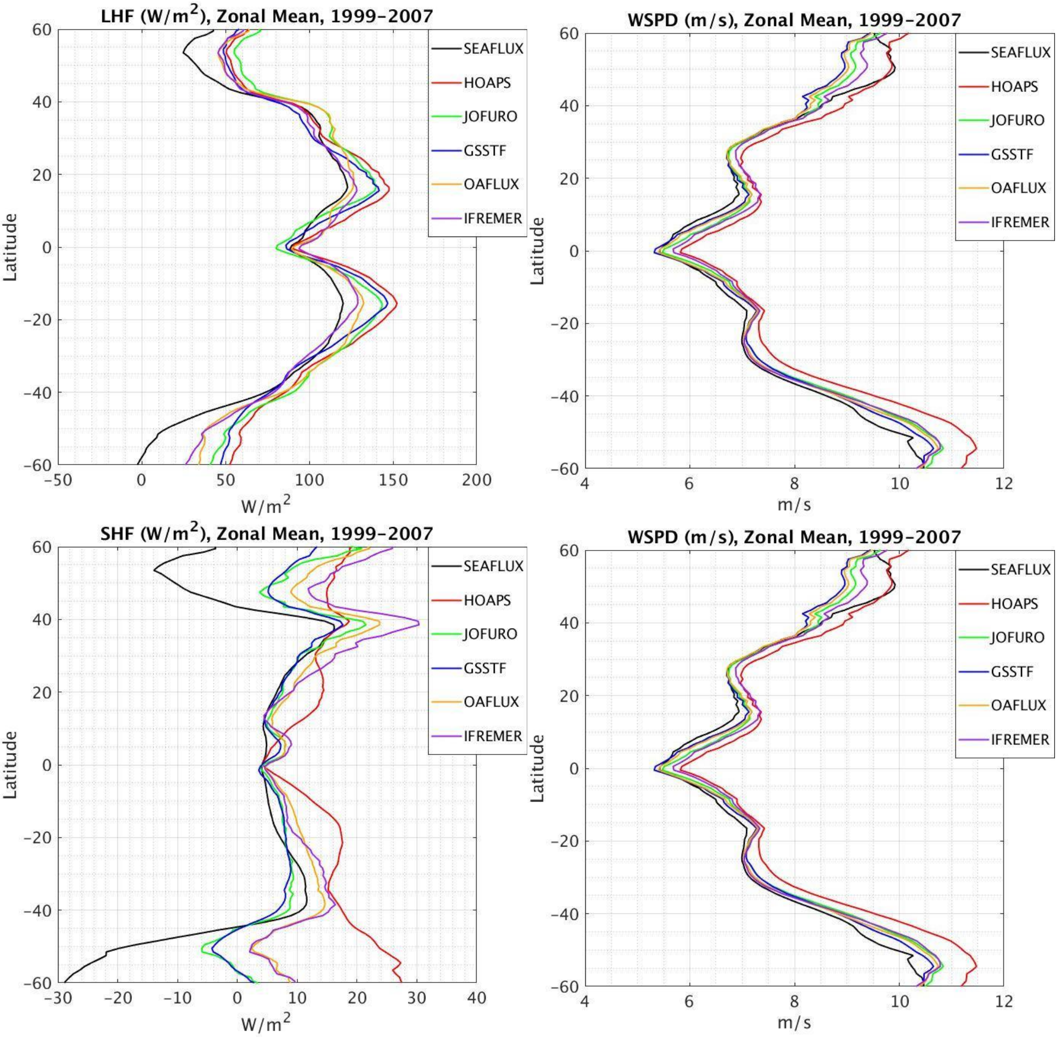
Product	Coverage	Spatial Resolution	Temporal Resolution	Variables	Reference	Comments
SeaFlux-CDR	1988-2017	0.25x0.25	3hr	LHF, SHF, U10, T10, Q10, SST	Clayson et al., 2016	Model-based interpolation; Earth Incidence Angle corrections; extended to SSMIS
OAFLux-V3	1985-2017	1x1	daily	LHF, SHF, U10, T10, Q10, SST	Yu et al., 2008	Uses Objective Analysis to fill in gaps, includes satellite and reanalysis inputs
HOAPS-v3.2	1987-2008;	0.5x0.5	6hr	LHF, SHF, U10, T10, Q10, SST	Fennig et al., 2012; Andersson et al., 2010	SSM/I-based near-surface meteorology; AVHRR Pathfinder SST; does not fill in missing data
GSSTF-v3	1987-2008;	0.25x0.25	daily	LHF, SHF, U10, T10, Q10, SST	Shie et al., 2012	Air temperature and sea surface temperature are from NCEP/DOE Reanalysis II
J-OFURO-v2-HF004	1988-2008;	1x1	daily	LHF, SHF, U10, T10, Q10, SST	Kubota and Tomita, 2007	Air temperature from NCEP/DOE Reanalysis II; SST from JMA MGDSST
IFREMER-v4	1999-2009;	0.25x0.25	daily	LHF, SHF, U10, T10, Q10, SST	Bentamy et al., 2013	Air temperature from ERA-Interim reanalysis; SST from OISST v2



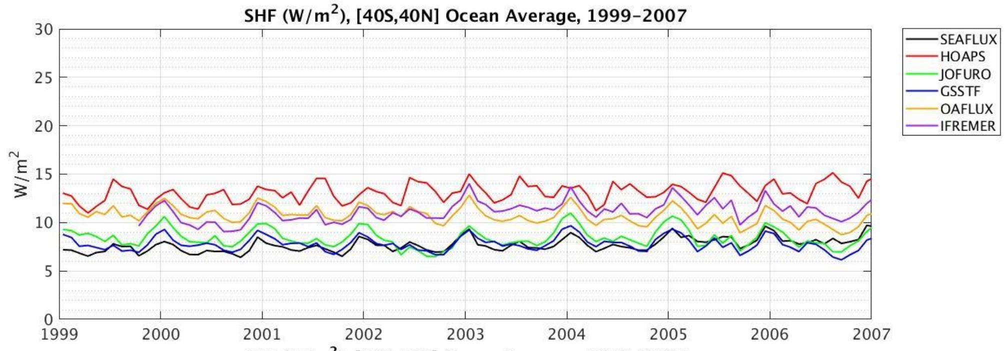
Annual Mean Pattern and Zonal Means

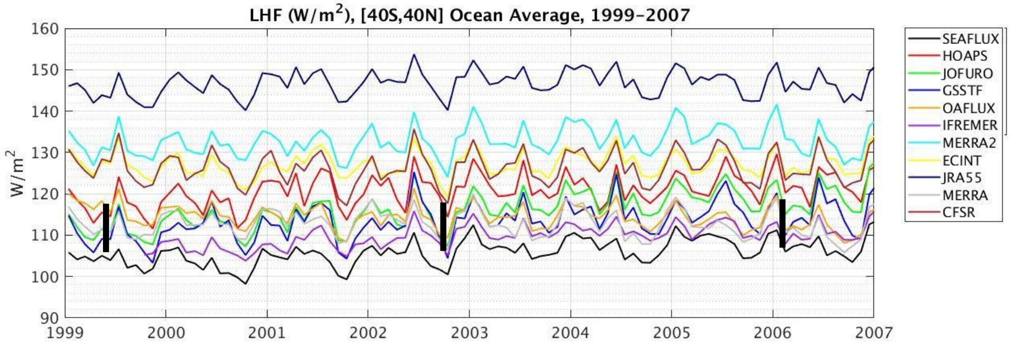
- Annual mean patterns are pretty similar between products; diverge mostly in terms of amplitude.
- Latent heat flux shows large divergence in both the tropics and extratropics but less so in the polar regions
  - Driven most strongly by Qair retrieval differences in the tropics; more strongly by wind speed in the midlatitudes
- Sensible heat flux show largest divergences as you move to higher latitudes
  - Driven most strongly by air temperature differences.

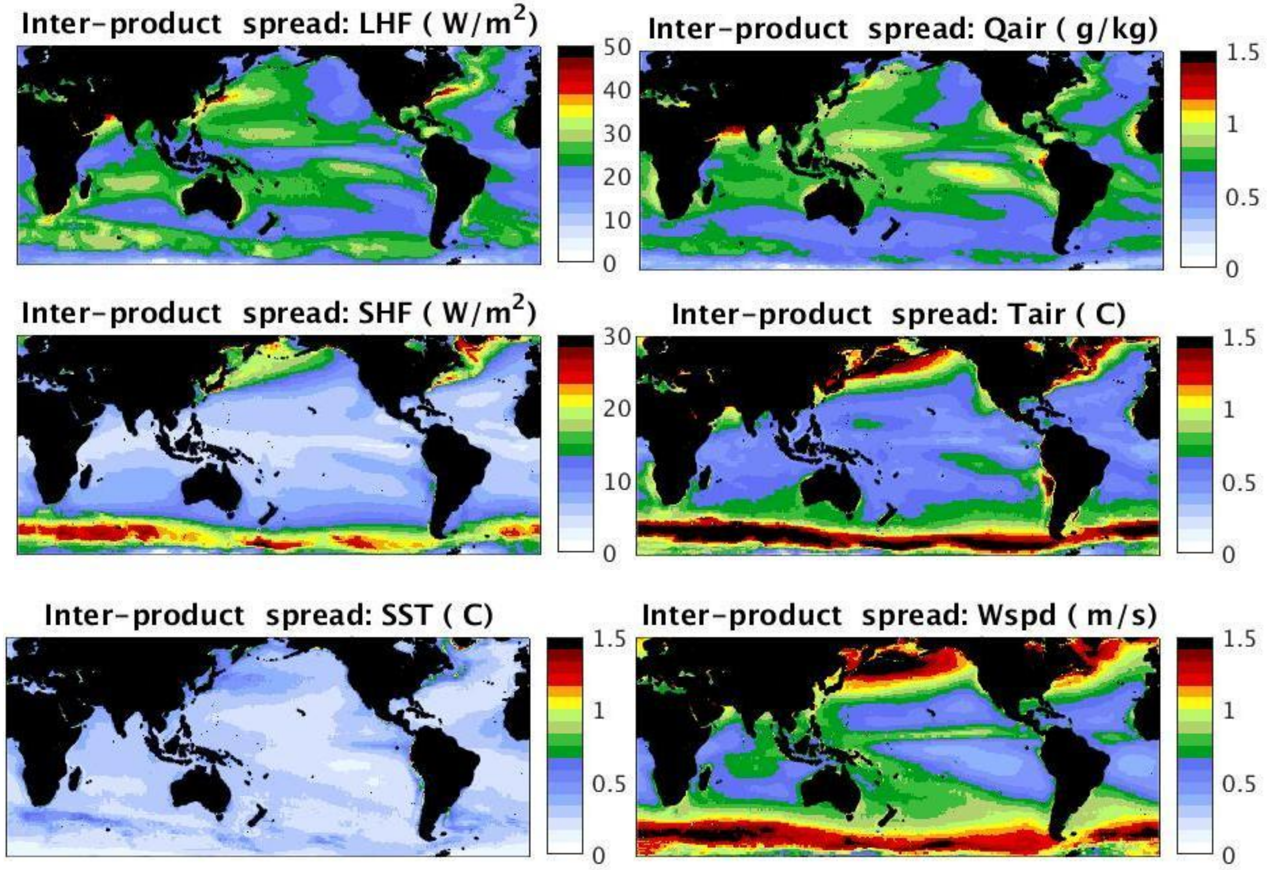
Annual Mean Pattern and Zonal Means

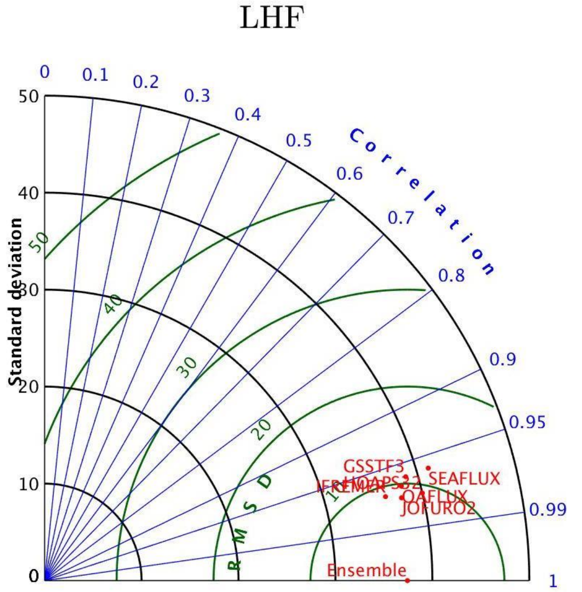


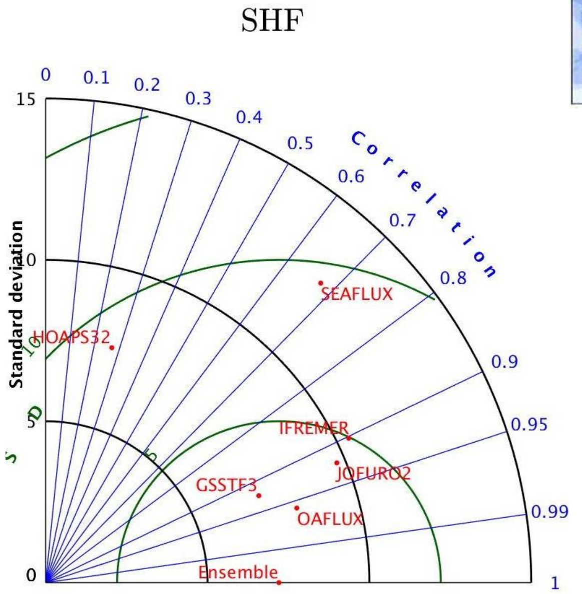
- Annual mean patterns are pretty similar between products; diverge mostly in terms of amplitude.
- Latent heat flux shows largest divergence in the subtropics and midlatitudes but less so in the deep tropics and polar regions
    - Zonal mean patterns controlled strongly by the global wind speed
- Sensible heat flux show largest divergences as you move to higher latitudes
    - Driven strongly by both wind speed and air temperature differences





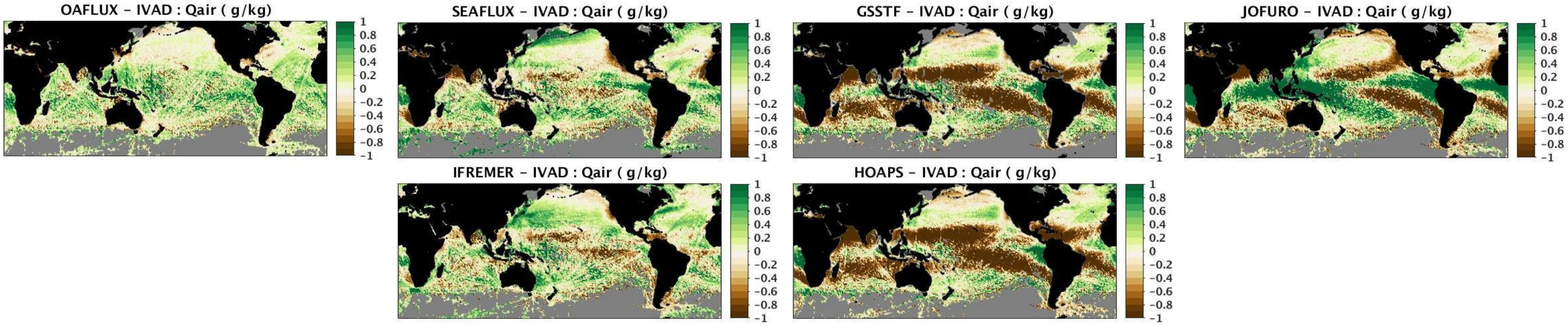




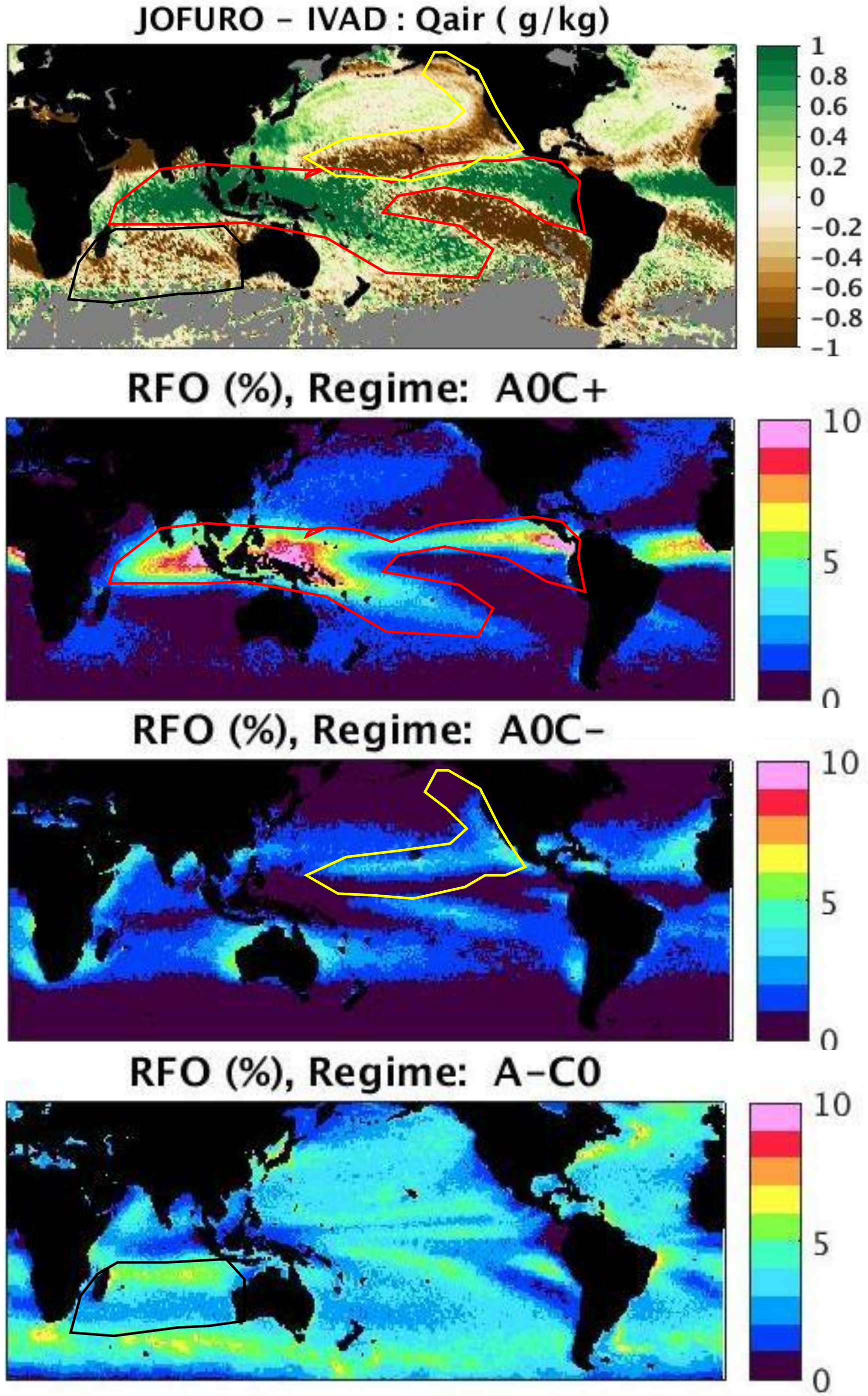


- Climate goal: 10 W/m^2 ocean surface *net* heat flux
- The satellite products show annual mean differences of 10-15 W/m^2 with respect to amplitude; they agree more closely in terms of annual cycle and interannual variability

Regional Biases



- The different products show strong regional patterns of biases in relation to surface observations (IVAD).
- GSSTF, HOAPS and JOFURO all show similar large scale patterns of bias, with strong regional signatures over the subtropical trade wind regimes and West Pacific STCZ. IFREMER v4 and SeaFlux-V1 show muted regional signature, but they are still evident



Retrieval Biases and Cloud Weather States

- The structure in the retrieval (Qa, top) biases appear to be co-aligned with patterns of cloud weather states (WS)
- WS are defined using ISCCP joint cloud top pressure / cloud-optical depth histograms.
- Large biases are seen in regions associated with deep convection and thick stratocumulus decks as you might expect

Real-Time Fluxes

Integrated Microwave Imager Fluxes

NFLUX

Intercomparison and Evaluation

Real-time turbulent fluxes

- The Integrated Multi-satellitE Retrievals for GPM (IMERG) includes a real-time data stream product
- While IMERG RT is focused on precipitation estimates, the Level 1C (intercalibrated) brightness temperatures from contributing passive microwave instruments are also included.
- *Thus, there is an opportunity to apply retrievals to these L1C data to estimate surface bulk variables and turbulent fluxes*

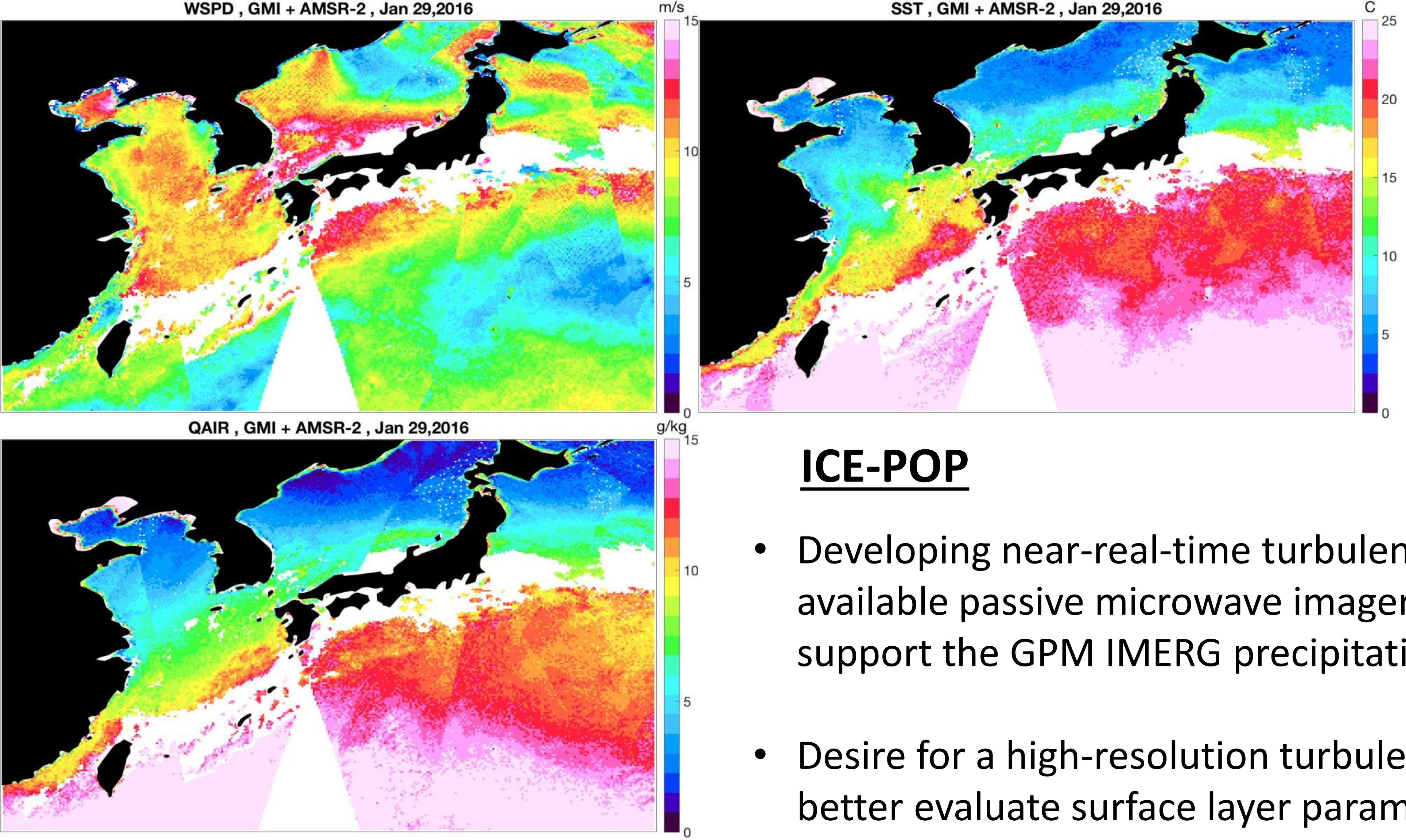
Platform(s)	Sensor	Freq	Freq	Freq	Freq	Freq	Freq	Freq	Freq
F16, ~~F17~~, F18,	SSMIS		19.35 V,H	22.235 V	37.0 V,H	91.665 V,H			
GPM	GMI	10.65 V,H	18.7 V,H	23.8 V	36.5 V,H	89.0 V,H	160.0 V,H	183.31 +/- (3,8)	
GCOM-W1	AMSR-2	10.65 V,H	18.7 V,H	23.8 V,H	36.5 V,H	89.0 V,H			
NPP	ATMS			23.8 QV	31.4 QV	88.2 QV	165.5 QH	183.31 +/- (1,1.8,3,4.5,7)	
Megha-Tropiques	SAPHIR							183.31 +/- (0.2, 1.1, 2.8, 4.2, 6.8, 11)	
NOAA-18, NOAA-19; METOP-A, METOP-B	MHS					89.0 QV	157.0 QV	183.31 +/- (1,3)	190.3 QV

Total Satellites: 11

SST

Precipitation, Cloud Liquid Water, Wind Speed, Water Vapor

Water Vapor, Clouds



ICE-POP

- Developing near-real-time turbulent heat fluxes from all available passive microwave imagers being archived to support the GPM IMERG precipitation product

- Desire for a high-resolution turbulent heat flux product to better evaluate surface layer parameterizations in NWP and their impact on precipitation forecasts.

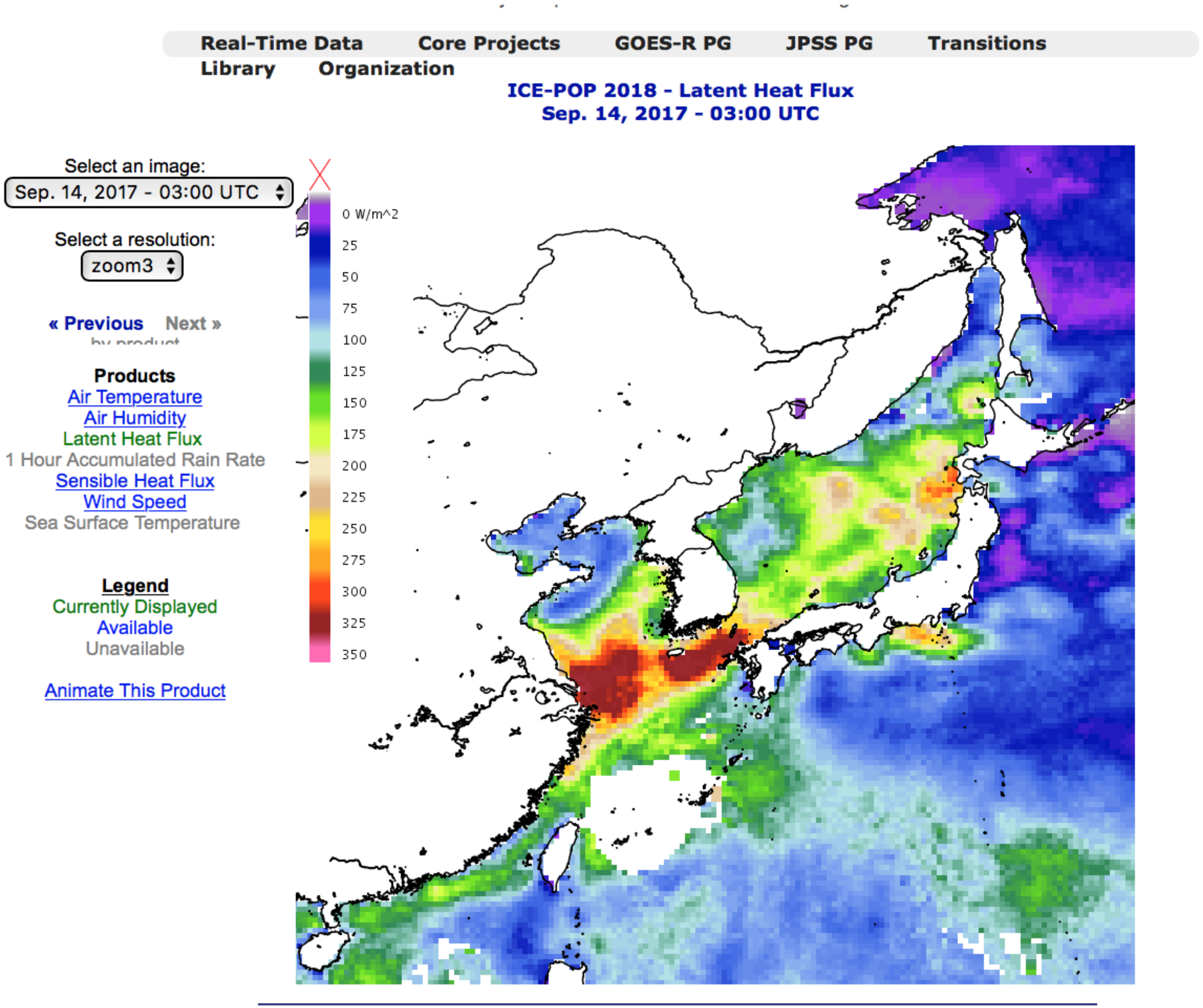
Product Distribution

Product Versions - Archive

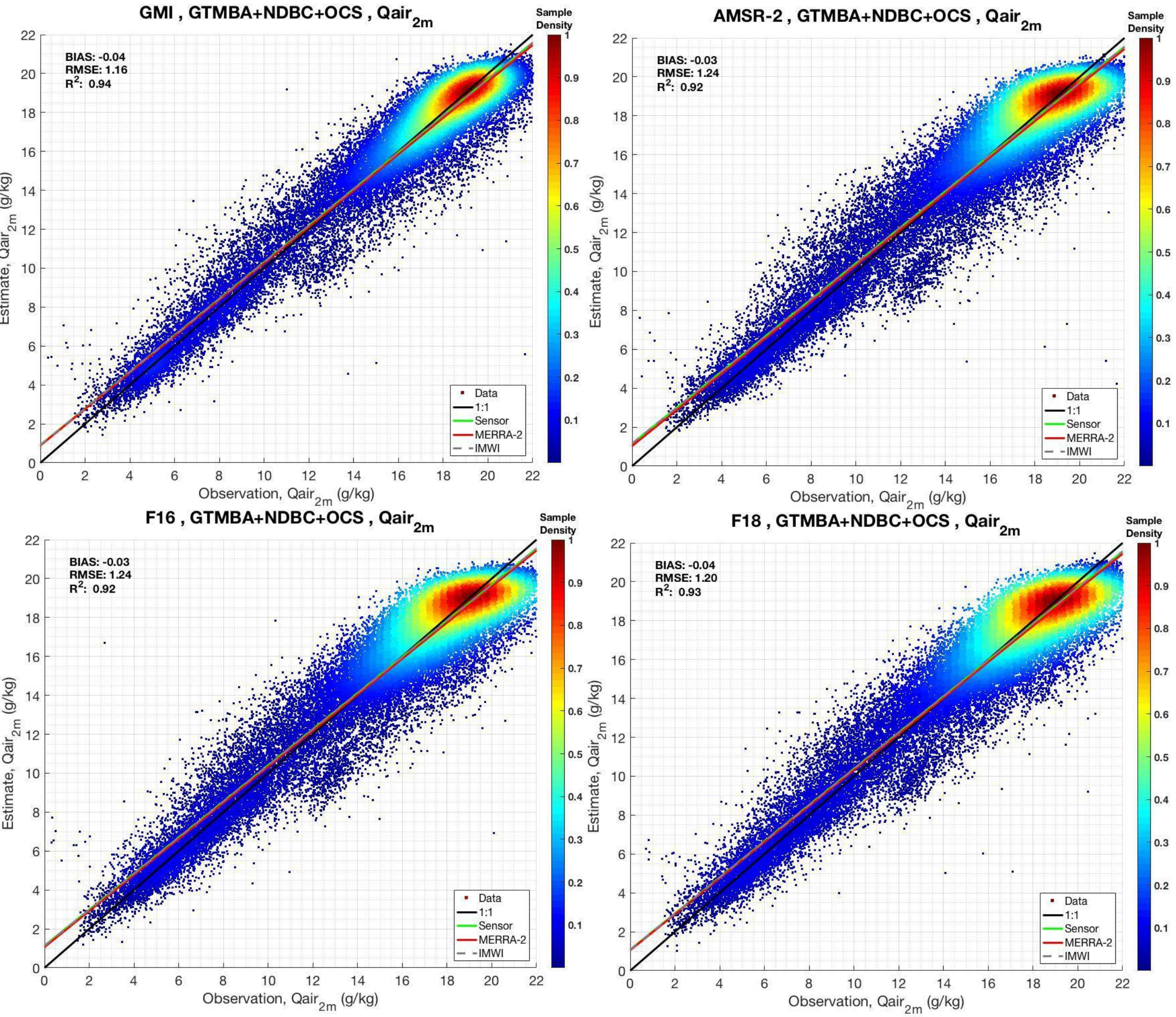
- *Level 3 , Global EASE-25km*
  - Hourly
  - Daily
  - Monthly
- *Level 3, ICE-POP Domain*
  - EASE-25km
  - 0.25x0.25 Equal-Angle
- Feb. 2014 - August 2017
- Upon request; served through FTP

Product Versions - Real-Time

- Hourly Updates
- Average of previous 24-hours
- Images available through web-portal
- Data available through FTP



Results - Neural Network Retrieval



Model

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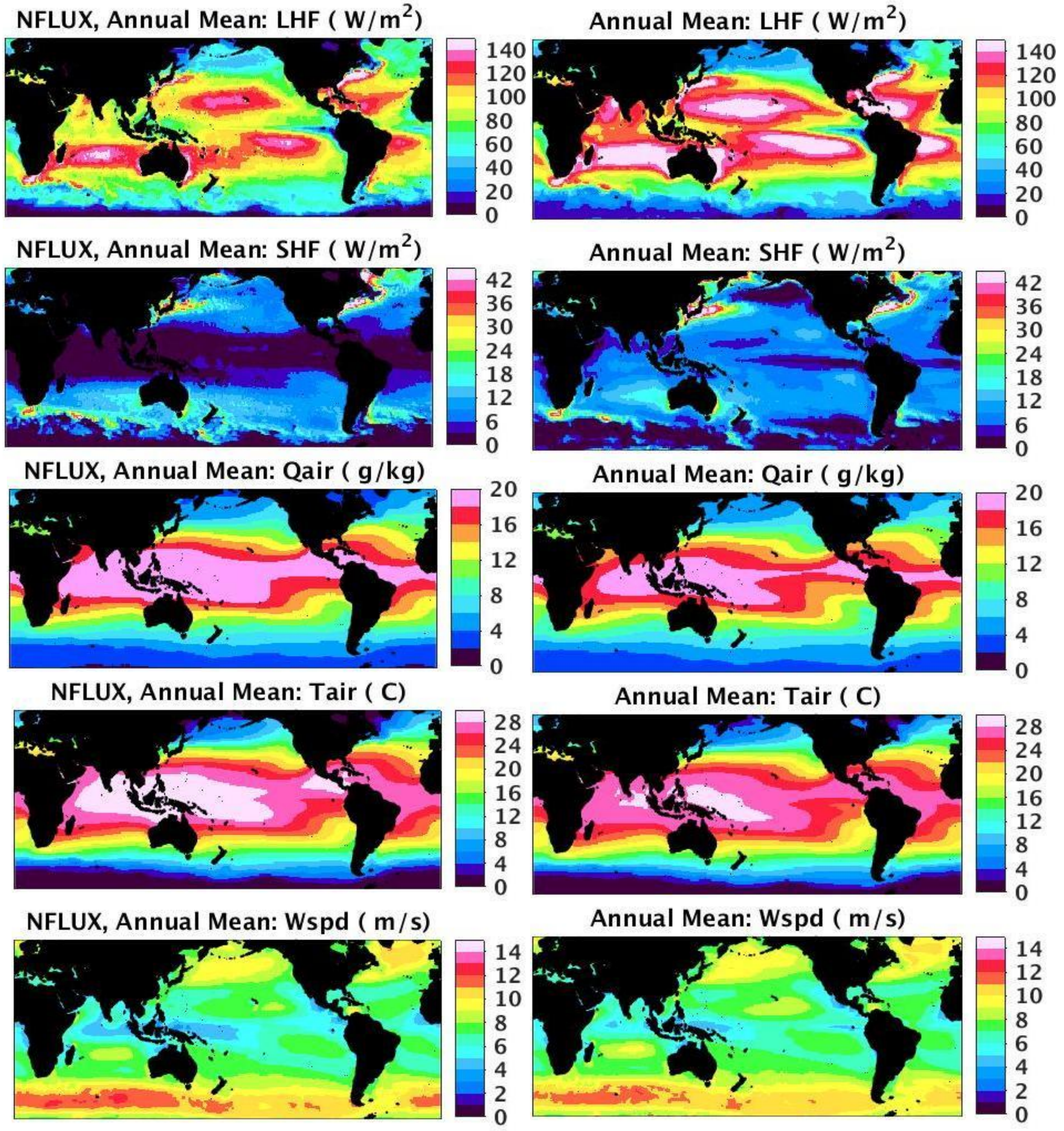
{37V-37H < 45K Masked}

Training

- Masking: Removes ~10% of all observations, 45K ~10th percentile of 37V-37H
- Results relative insensitive to training algorithm and observational splitting into Training/Cross-Validation/Testing sets

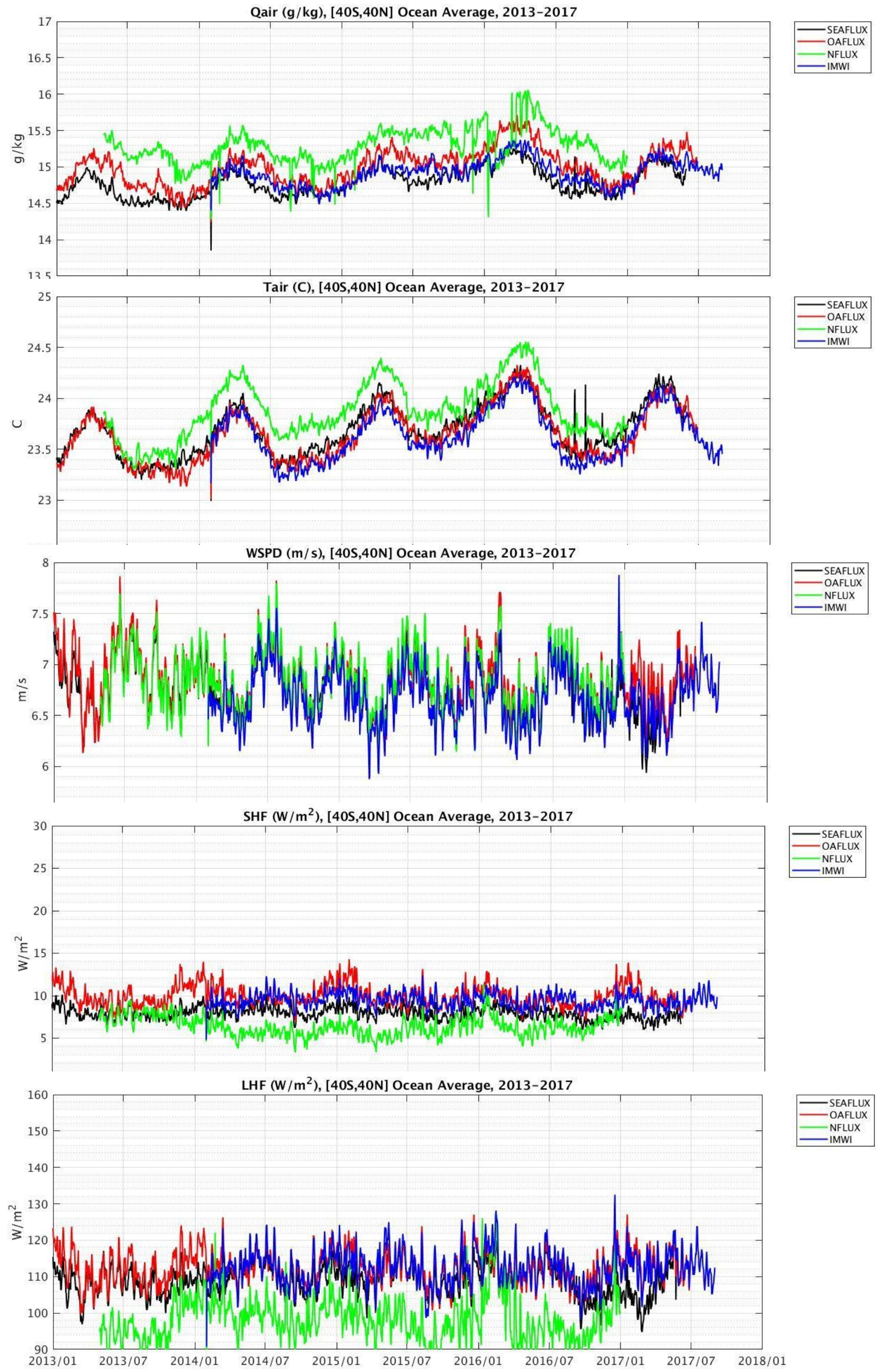
Performance

- R^2 ~0.9 or better for all parameters
- Small bias and RMSE ~1.2 (g/kg, C, m/s) for all parameters
- Some outliers made it through the automated QC of buoys



N-FLUX

- NRL has developed real-time fluxes using a similar set of passive microwave observations including microwave sounders
- N-FLUX takes additional steps to gap-fill missing observations to support modeling applications
- Large-scale patterns are generally similar to the ensemble mean of climate-scale products; differences are primarily related to overall amplitudes



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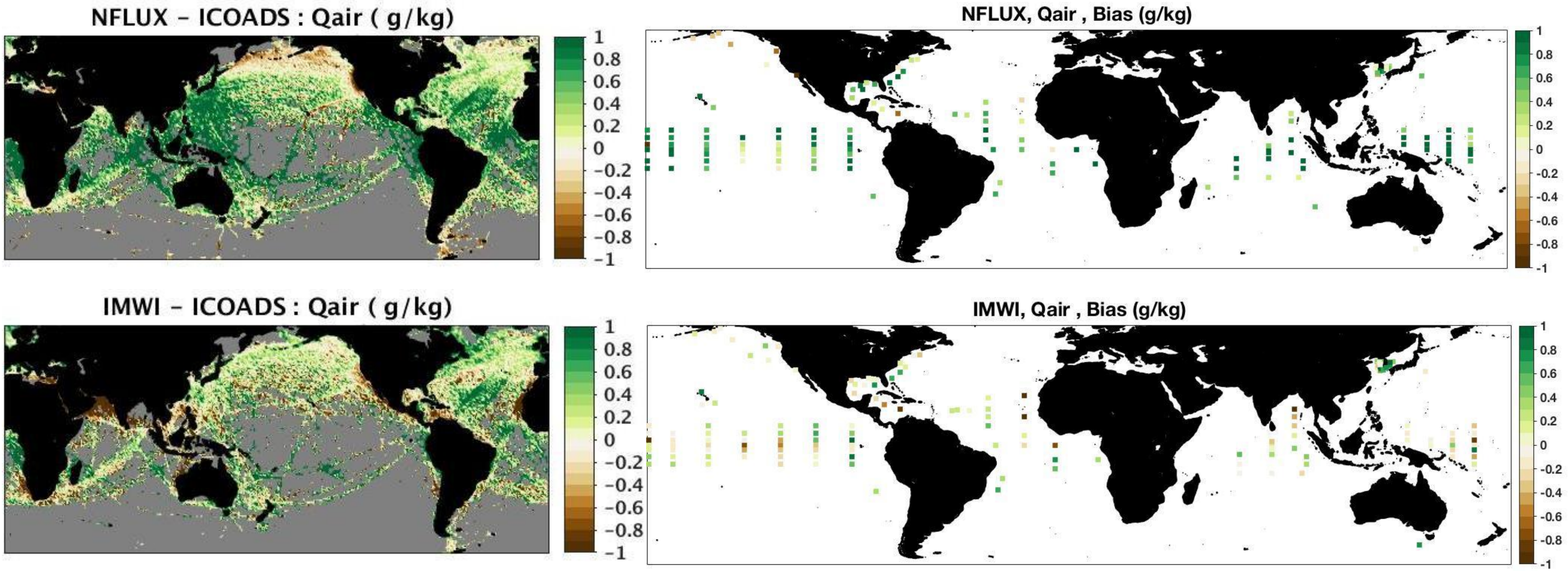
- Large-scale patterns are generally similar to the ensemble mean of climate-scale products; differences are primarily related to overall amplitudes
- NFLUX Qair and Tair estimates appear biased higher than IMWI and other climate products

Regional Biases



- Both NFLUX and IMWI appear to have similar bias patterns to OAFLUX and SeaFlux
  - NFLUX Qair appears to have a moist tropical bias
  - IMWI biases are similar to those found in SeaFlux but are somewhat reduced in amplitude.
- It becomes problematic to globally validate real-time products using surface observations over a short period.

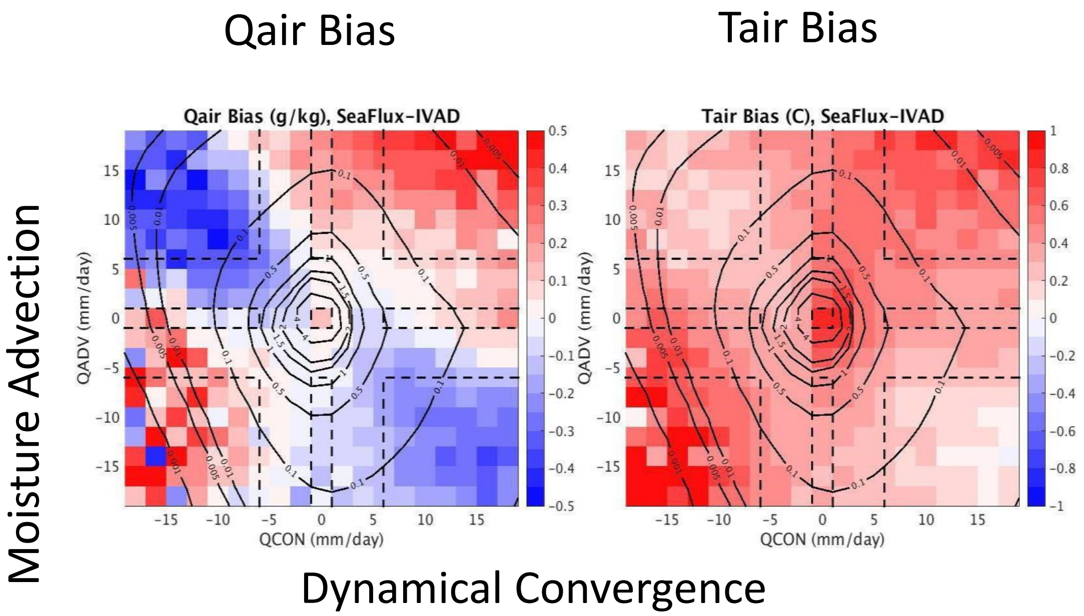
Future

Algorithm Improvements

New Sensors

Data Fusion

Directions forward: understanding/correcting state errors

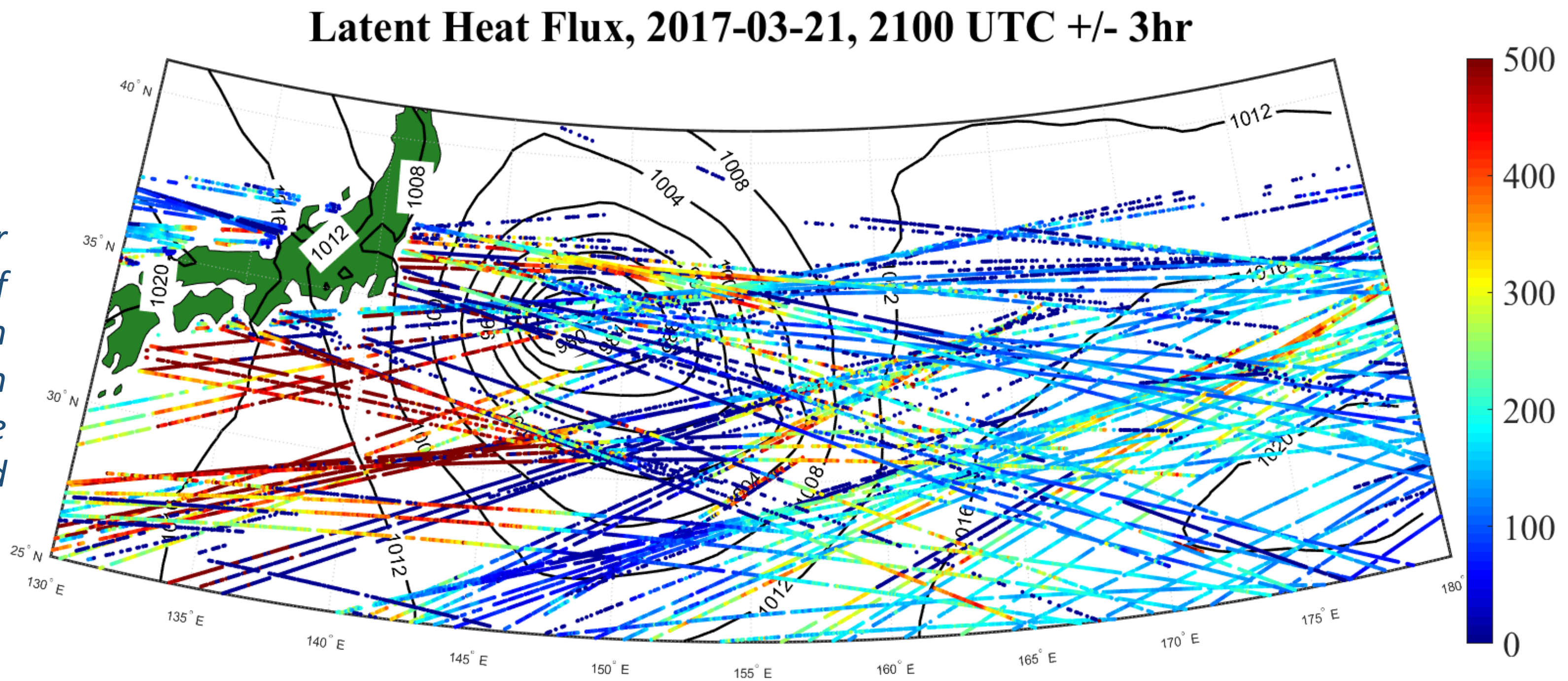


- Strong regional patterns of biases related to surface observations
- Strength depends on product, but similar patterns across all
- Error fields depend on weather state

Directions forward: new sensors

- Qair/Tair: “Hyperspectral” Microwave Atmospheric Sounding (HyMAS), TROPICS
  - Accuracy in cloudy conditions may approach those of AIRS/AMSU in clear conditions
  - Provide sub-boundary layer information

- Winds: CYGNSS
  - Provide very frequent surface wind observations
  - Provide winds under adverse weather (very cloudy/heavy rain scenes) that are currently masked



Provided by J. Crespo (U. Mich) and D. Posselt (NASA JPL)
Example of latent heat flux product being developed under the CYGNSS Science Team. This uses a preliminary set of developmental CYGNSS L2 winds (v1.1) together with reanalysis-based surface moisture. The CYGNSS winds can provide wind observations under all-sky conditions where microwave imagers are typically rain flagged. An updated release of winds is expected soon.

Directions forward: data fusion

- Develop new techniques for data fusion

- Example: Kalman Filter

$$x_a = x_b + W(x_o - x_b) = x_b + W(s_e - x_b)$$
$$W = \frac{\sigma_b^2}{\sigma_b^2+\sigma_o^2} = \frac{\sigma_b^2}{\sigma_b^2+\sigma_e^2}$$

  - Approach can be used to both fill in data gaps as well merge mutliple estimates of near-surface parameters
  - Provides a framework to easily incorporate new sensors/retrievals (e.g. scatterometer L2 winds)

Summary

- The turbulent heat fluxes, and surface evaporation in particular, are a substantial source of uncertainty in current global energy and water cycle budgets
- Estimates of these fluxes at the global scale requires use of satellites; however retrievals of the near-surface quantities remain problematic. This is fundamentally related to an inability of current sensors to resolve sub-boundary layer thermodynamic information.
- However, new approaches to regime-dependent biases and data fusion can and are being developed to mitigate these issues. Incorporation of future sensors will also benefit from this on-going development.
- Together, these approaches are leading to new climate data records and real-time products that can be valuable to a number of applications, depending on the spatio-temporal resolution and accuracy requirements